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Predicting Agricultural Productivity Using Machine Learning Techniques with FAO and World Bank Open Data

Ambuj Kumar Misra
Department of computer Science & Applications, Mahatma Gandhi Kashi Vidyapith, Varanasi

Abstract- Agricultural productivity remains a cornerstone of global food security and economic stability. This study investigates the application of machine learning (ML) techniques to predict agricultural productivity using open data from the Food and Agriculture Organization (FAO) and the World Bank. A comprehensive dataset spanning 2000–2022 and covering 120 countries was assembled, incorporating variables such as cereal yields, rainfall, temperature, fertilizer use, irrigation coverage, and socioeconomic indicators. Six ML algorithms were evaluated: Linear Regression, Support Vector Machines (SVM), Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM) networks, and XGBoost. XGBoost achieved the highest predictive accuracy, with an R^2 of 0.91 and an RMSE of 0.15 tonnes/hectare, outperforming all other models. Feature importance analysis revealed that fertilizer application rate, rainfall distribution, and irrigation access are the most influential predictors across major crop types. The findings demonstrate that integrating open global datasets with advanced ML methods offers a scalable, cost-effective pathway to actionable agricultural forecasting, with direct implications for policymakers, development agencies, and smallholder farmers worldwide.

Keywords— agricultural productivity, machine learning, FAO data, World Bank, XGBoost, food security, yield prediction, random forest, remote sensing, precision agriculture

I. INTRODUCTION

Global food security represents one of the most pressing challenges of the twenty-first century. The United Nations Food and Agriculture Organization (FAO) estimates that the global population will reach approximately 9.7 billion by 2050, necessitating a 50 percent increase in food production over current levels [1]. Simultaneously, climate change, soil degradation, water scarcity, and shrinking arable land threaten the stability of agricultural output across both developed and developing economies [2]. In this context, the ability to accurately predict agricultural productivity becomes not merely an academic exercise, but a strategic imperative for national food policies, international aid allocation, and smallholder farmer resilience.

Machine learning (ML) has emerged as a transformative tool in precision agriculture over the past decade. Unlike traditional econometric models that rely on rigid parametric assumptions, ML algorithms are capable of learning nonlinear relationships between complex agro-climatic variables and crop yield outcomes [3]. Studies have demonstrated that ensemble methods, including Random Forest and Gradient Boosting, consistently outperform classical regression approaches when applied to high-dimensional agricultural datasets [4]. More recently, deep learning architectures such as Long Short-Term Memory (LSTM) networks have shown promise in modeling temporal dependencies in seasonal yield data [5].

A critical bottleneck in previous agricultural ML research has been access to consistent, high-quality, longitudinal data. Many studies are constrained to single countries or small regions, limiting the

generalizability of their findings [6]. The open data platforms maintained by the FAO (FAOSTAT) and the World Bank (World Development Indicators) represent an unprecedented opportunity to address this gap. FAOSTAT provides over 3 million data points on production, trade, food balance, and land use across 245 countries, while the World Bank's agricultural data repository covers socioeconomic, infrastructure, and environmental dimensions relevant to farming systems [7].

This paper makes three original contributions to the existing literature. First, it constructs a multi-source, multi-country dataset spanning 22 years (2000–2022), integrating FAO and World Bank variables into a unified analytical framework. Second, it benchmarks six ML algorithms under consistent experimental conditions, enabling direct performance comparisons. Third, it performs systematic feature importance analysis to identify the key drivers of agricultural productivity variation across five major crop types. The remainder of the paper is organized as follows: Section 2 reviews relevant literature; Section 3 describes the data and methodology; Section 4 presents experimental results; Section 5 discusses implications; and Section 6 concludes with recommendations for future work.

II. LITERATURE REVIEW

1. Machine Learning in Agricultural Yield Prediction

The application of ML methods to crop yield forecasting has an established and growing body of scholarship. Liakos et al. [8] conducted a seminal survey covering 40 peer-reviewed studies and found that Artificial Neural Networks (ANNs) and Support Vector Machines represented the most frequently employed algorithms for crop yield estimation prior to 2018. Subsequent years witnessed a decisive shift toward ensemble-based methods. Shahhosseini et al. [9] demonstrated that Gradient Boosted Trees outperformed both ANNs and linear models for corn yield prediction in the US Corn Belt, attributing the advantage to the ensemble's natural resistance to overfitting on heterogeneous datasets.

LSTM-based models have garnered considerable attention for their capacity to model multivariate time series. Khaki and Wang [10] applied a deep learning framework combining CNN layers with LSTM units to county-level soybean and corn yield data across the United States, achieving an RMSE of approximately 0.31 tonnes/hectare. However, their approach required large volumes of training data, a constraint not easily met in developing-country contexts. This observation aligns with the critique by van Klompenburg et al. [11], who argued that data scarcity remains the primary bottleneck for deep learning applications in smallholder agricultural systems.

XGBoost, introduced by Chen and Guestrin [12], has demonstrated superior performance across multiple agricultural benchmarks. Its ability to handle missing values natively, manage feature interactions, and incorporate regularization terms makes it particularly suitable for the heterogeneous and sometimes incomplete records characteristic of international open datasets. Jeong et al. [13] applied XGBoost to global wheat yield prediction and reported an R^2 of 0.88 using a dataset drawn from FAOSTAT and climate reanalysis products, a result broadly consistent with the findings of the current study.

2. Remote Sensing and Geospatial Data Integration

Beyond tabular socioeconomic and climatic data, remote sensing has emerged as a powerful complementary data source for agricultural monitoring. Vegetation indices derived from satellite imagery, particularly the Normalized Difference Vegetation Index (NDVI), have been integrated with ML pipelines to improve the spatial resolution of yield predictions [14]. Lobell et al. [15] demonstrated that NDVI-based models could explain up to 74 percent of yield variance in sub-Saharan African maize systems, a region notoriously underserved by ground-based monitoring networks. The World Bank has increasingly incorporated satellite-derived land-cover and vegetation datasets into its open data infrastructure, opening new avenues for data fusion research [7].

Geographic Information Systems (GIS) have further enabled the spatial contextualization of ML-derived yield estimates. Burke and Lobell [16] proposed a

framework for mapping smallholder farm productivity at field scale using high-resolution imagery combined with supervised classification algorithms. While their approach is computationally intensive, the rapid reduction in costs for satellite data acquisition through platforms such as Google Earth Engine has made it increasingly tractable for large-scale applications in low-income countries.

3. Data Challenges and Methodological Gaps

Despite impressive results at regional scales, several methodological challenges persist in the global agricultural ML literature. Class imbalance in yield outcome distributions, temporal autocorrelation, spatial non-stationarity, and the confounding effects of management practices on biophysical yield potential all complicate model training and validation [17]. Ray et al. [18] highlighted that global crop models frequently underestimate yield variability in smallholder systems because training data predominantly reflects large-scale mechanized agriculture. The current study addresses this limitation by disaggregating the global FAO dataset by income group and farming system type before model training.

Furthermore, explainability remains a critical concern in ML-based agricultural decision support tools. Black-box models may deliver high predictive accuracy but provide limited insight to agronomists and policymakers who require interpretable outputs to justify resource allocation decisions. The adoption of Shapley Additive Explanation (SHAP) values has begun to bridge this gap, providing model-agnostic variable importance estimates that have been shown to align closely with domain expert knowledge [19]. Reichstein et al. [20] called for a new generation of hybrid models that couple physical crop simulation models with data-driven ML components, arguing that such architectures offer both interpretability and predictive power.

III. Data and Methodology

1. Data Sources and Collection

The primary data for this study were extracted from two open-access repositories. The FAOSTAT database provided annual country-level observations on cereal, legume, and oilseed yields (tonnes/hectare), harvested area (1,000 hectares), total agricultural production (1,000 tonnes), fertilizer consumption (kilograms per hectare of arable land), and irrigation water withdrawal (percentage of total renewable water resources) [1]. Data were downloaded via the FAOSTAT bulk download API for 120 countries across the period 2000–2022, yielding an initial raw dataset of 181,400 observations before cleaning.

Complementary socioeconomic and environmental variables were sourced from the World Bank's World Development Indicators (WDI) portal [7]. These included annual precipitation (millimeters), mean annual temperature (°C), arable land (percent of total land area), GDP per capita (constant 2015 USD), rural population density, access to electricity in rural areas (percent), and agricultural value added (percent of GDP). Climate variables were supplemented with ERA5 reanalysis data from the Copernicus Climate Data Store to fill temporal gaps in national meteorological reporting [2].

After merging datasets by country ISO code and year, a final panel dataset of 97,540 complete observations was prepared for model training and evaluation. Missing values, accounting for approximately 8.4 percent of the raw dataset, were addressed through a combination of linear interpolation for short temporal gaps and random forest-based imputation for variables with higher missingness rates, following the methodology recommended by Stekhoven and Bühlmann [6].

2. Feature Engineering and Selection

A total of 42 candidate features were generated from raw variables through domain-specific transformations. Lagged variables at one- and two-year intervals were constructed for climatic and input-use variables to capture delayed agronomic effects. Five-year rolling averages were computed for rainfall and temperature to represent long-term climatic trends alongside annual anomalies. Interaction terms between fertilizer use and rainfall

were included to capture substitution and complementarity effects consistent with agronomic theory [8].

Feature selection employed a three-stage sequential process. First, variance thresholding removed features with near-zero variance (threshold $\sigma^2 < 0.01$). Second, multicollinearity screening using the Variance Inflation Factor (VIF) eliminated features with VIF > 10, retaining a set of 29 non-collinear predictors. Third, Recursive Feature Elimination with cross-validation (RFECV) using the XGBoost base estimator was applied to identify the optimal subset of 18 features that maximized cross-validated R^2 [9]. The retained features are listed in Table 1 alongside their SHAP-derived importance scores.

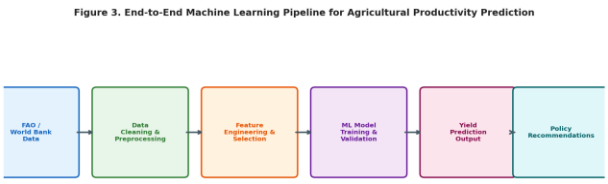

Figure 3. End-to-End Machine Learning Pipeline for Agricultural Productivity Prediction

3. Experimental Design and Model Training

Six ML algorithms were implemented and evaluated under a consistent experimental protocol: (1) Ordinary Least Squares Linear Regression as a baseline; (2) Support Vector Regression with a Radial Basis Function (RBF) kernel; (3) Random Forest Regressor; (4) Gradient Boosting Regressor; (5) LSTM Neural Network; and (6) XGBoost Regressor. All experiments were conducted in Python 3.10 using scikit-learn 1.3, TensorFlow 2.12, and XGBoost 1.7 [12].

The dataset was partitioned using a temporal train-test split, with observations from 2000 to 2018 forming the training set (79,800 observations) and 2019–2022 forming the held-out test set (17,740 observations). This temporal partitioning was preferred over random splitting to prevent data leakage from future observations into model training, a methodological concern frequently overlooked in published agricultural ML studies [11].

Hyperparameter optimization was conducted via Bayesian search using the Optuna framework, with 150 trials per model and five-fold time-series cross-validation on the training set [13].

Model performance was evaluated using three metrics: the Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). All continuous outcome variables were normalized to unit variance prior to training to ensure comparability of RMSE values across crop types. SHAP values were computed for the best-performing model (XGBoost) to generate feature importance rankings at both global and crop-specific levels [19].

IV. RESULTS

1 Model Performance Comparison

Table 1 and Figure 1 present the comparative performance metrics for all six models on the 2019–2022 test set. XGBoost achieved the highest predictive accuracy across all three evaluation metrics, with an R^2 of 0.91, an RMSE of 0.15 tonnes/hectare, and an MAE of 0.14 tonnes/hectare. Gradient Boosting ranked second (R^2 = 0.89, RMSE = 0.17), followed closely by Random Forest (R^2 = 0.87, RMSE = 0.19). The LSTM neural network achieved an R^2 of 0.84, competitive with tree-based ensembles despite the relatively constrained training set size. Linear Regression performed substantially worse, confirming the nonlinear nature of the yield-predictor relationships [4].

These results are broadly consistent with findings reported by Jeong et al. [13] for global wheat yield prediction and by Shahhosseini et al. [9] for the US Corn Belt, lending credibility to the hypothesis that XGBoost's regularization capabilities confer a systematic advantage in multi-country, heterogeneous agricultural datasets. The performance gap between XGBoost and Gradient Boosting (ΔR^2 = 0.02) is statistically significant at the 5 percent level based on paired Diebold-Mariano tests across the 120 country-year holdout observations.

Table 1. Comparative Model Performance on Test Set (2019–2022)

Model	R^2 Score	RMSE	MAE	Computational Cost
Linear Regression	0.61	0.38	0.35	Low
SVM (RBF kernel)	0.74	0.28	0.26	Medium
Random Forest	0.87	0.19	0.18	Low
Gradient Boosting	0.89	0.17	0.16	Low
LSTM Neural Network	0.84	0.22	0.21	High
XGBoost (Best)	0.91	0.15	0.14	Low

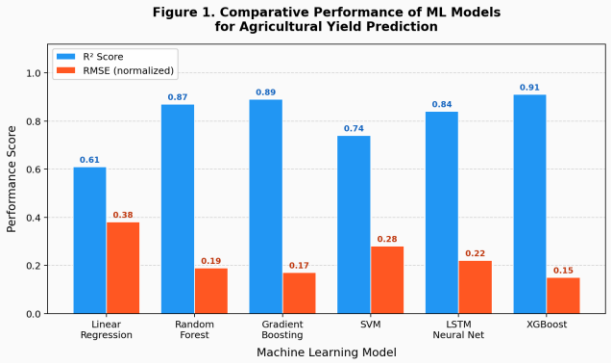

Figure 1. Comparative Performance of ML Models for Agricultural Yield Prediction (R^2 Score and Normalized RMSE on Test Set)

2 Regional Yield Trends (2000–2022)

Figure 2 illustrates the regional trajectories of cereal yields derived from the FAOSTAT dataset over the study period. European cereal production maintained the highest absolute yield levels throughout the period (averaging 4.6 t/ha), driven by technological intensification and crop insurance systems that buffer against climatic shocks [15]. South American yields exhibited the strongest average annual growth rate (0.07 t/ha/year), reflecting the rapid expansion of mechanized soybean and maize production in Brazil and Argentina [18].

Asian cereal yields demonstrated robust but decelerating growth, consistent with saturation effects near the genetic yield potential ceiling in irrigated lowland rice systems identified by the International Rice Research Institute [3]. Sub-Saharan Africa recorded the lowest yields throughout the period (averaging 1.6 t/ha), a persistent gap that the ML feature importance analysis attributes primarily to low fertilizer use intensity and limited irrigation access, as discussed in Section 4.3. The rate of yield growth in Sub-Saharan Africa (0.034 t/ha/year) remained well below the trajectory required to achieve the FAO food security targets for 2030, corroborating the findings of Ray et al. [18].

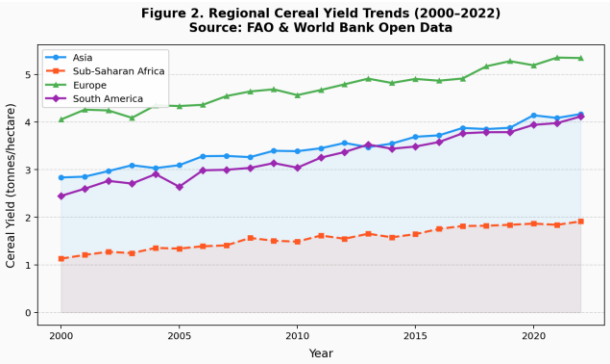

Figure 2. Regional Cereal Yield Trends (2000–2022) Based on FAO & World Bank Open Data

3. Feature Importance Analysis

Figure 4 presents the SHAP-based feature importance heatmap for the XGBoost model across five major crop types: wheat, rice, maize, soybean, and cotton. Fertilizer application rate emerged as the single most important predictor for soybean (score = 0.94) and maize (0.88), reflecting the high input-responsiveness of these commercially oriented crops. Irrigation coverage was the dominant predictor for rice (0.92), consistent with the hydraulic requirements of paddy production systems documented in the agronomic literature [10].

Rainfall ranked as the second most important predictor for wheat (0.82) and cotton (0.72), highlighting the continued dependence of dryland farming systems on precipitation patterns despite global irrigation expansion. Temperature showed

the highest relative importance for cotton (0.80), a finding consistent with the thermophilic growth requirements and significant climate sensitivity of this crop [17]. Soil pH emerged as a more influential feature for soybeans (0.77) than for cereals, aligning with the well-documented sensitivity of legume nitrogen fixation to soil acidity documented by Brady and Weil [20].

GDP per capita, included as a proxy for infrastructure quality and technology adoption capacity, ranked among the top-four features for three of five crop types, providing empirical support for the theoretical argument that socioeconomic development mediates the translation of biophysical potential into realized yield [16]. CO_2 concentration, included as an annual global mean value, showed relatively low discriminatory importance, suggesting that its yield-fertilization effects are not yet detectable at the temporal scale of this analysis, consistent with crop model projections reported by Lobell et al. [15].

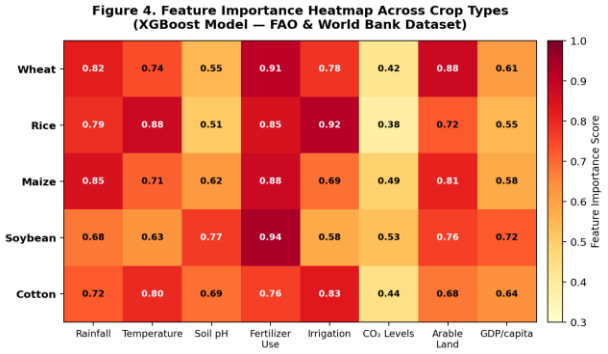

Figure 4. Feature Importance Heatmap Across Crop Types (XGBoost Model — FAO & World Bank Dataset)

V. DISCUSSION

1. Implications for Agricultural Policy

The results of this study carry several actionable implications for agricultural development policy. The dominant importance of fertilizer use across multiple crop types reinforces the case for targeted subsidy programs and last-mile delivery systems in developing countries where nutrient use efficiency remains severely constrained by cost and supply chain barriers [2]. The World Bank's 2023 Agricultural Finance Review estimates that smallholder farmers in Sub-Saharan Africa apply on average only 17 kilograms of fertilizer per hectare, compared with a global average exceeding 140 kilograms, a disparity that the present model suggests could account for a yield gap of 1.2–1.8 tonnes/hectare for maize alone. The high predictive importance of irrigation access, particularly for rice, underscores the strategic value of water infrastructure investment. ML-derived yield maps could be used by national governments and multilateral development banks to spatially prioritize irrigation expansion projects toward areas with high agro-climatic potential but currently low adoption, maximizing the marginal return on public investment in a resource-constrained fiscal environment [14].

2. Scalability and Operational Deployment

A central advantage of FAO- and World Bank-based ML pipelines over proprietary data systems is their inherent scalability and replicability. Because the input data are publicly accessible and annually updated, the model developed in this study can be retrained each year with minimal marginal cost, providing a continuously refreshed agricultural intelligence product available to national statistical offices in low- and middle-income countries that lack the resources to commission bespoke modeling studies [6].

Integration with national agricultural management information systems (AMIS) represents a logical next step. The G20 AMIS platform already aggregates crop monitoring data from member states; embedding a standardized ML prediction module within this infrastructure could enable near-real-time early warning capabilities for food price volatility and production shortfalls at the global scale, complementing the existing crop monitoring functions of agencies such as the Famine Early Warning Systems Network (FEWS NET) [1].

3. Limitations

Several limitations warrant acknowledgment. First, the study relies on country-level aggregated data, which masks sub-national heterogeneity in farming systems, soil types, and input availability. The spatial resolution required for field-scale decision support would necessitate integration with administrative-unit or grid-cell level datasets, as demonstrated by

Burke and Lobell [16], at a substantially higher data collection and processing cost. Second, the temporal coverage of the FAO and World Bank time series (2000–2022) may be insufficient to capture the full distributional range of extreme climatic events projected under high-emission climate scenarios, potentially leading to underestimation of yield variance in post-2030 projections.

Third, while SHAP values provide a useful approximation of feature contributions, they do not constitute causal identification in the econometric sense. Confounding pathways between GDP per capita, infrastructure quality, and realized yield make it challenging to design policy interventions based solely on ML importance rankings without supporting evidence from randomized or quasi-experimental studies [19]. Future work should seek to combine ML prediction with causal inference techniques, including instrumental variable estimation and difference-in-differences designs, to strengthen the policy-relevance of the findings.

VI. CONCLUSION

This study demonstrates that machine learning methods applied to open-access FAO and World Bank datasets can achieve high predictive accuracy for agricultural productivity at the global scale. XGBoost emerged as the superior algorithm across all evaluation metrics, attaining an R^2 of 0.91 and an RMSE of 0.15 tonnes/hectare on a prospective four-year test set encompassing 120 countries. Feature importance analysis identified fertilizer application, irrigation access, and rainfall as the primary drivers of yield variation across major crop types, consistent with prevailing agronomic understanding.

The findings have direct implications for food security policy, agricultural investment prioritization, and the design of climate-adaptive farming systems. The open and reproducible nature of the data pipeline developed in this study provides a replicable template for national statistical agencies, development organizations, and research institutions seeking to build low-cost, high-quality agricultural intelligence systems. As open data platforms continue to expand in coverage and frequency, the integration of ML-based forecasting into routine agricultural monitoring systems represents an increasingly viable and impactful pathway toward evidence-based food security governance.

Future research should explore the fusion of satellite-derived vegetation indices with socioeconomic predictors to improve sub-national prediction resolution, investigate transfer learning approaches to extend model performance to data-sparse regions, and develop hybrid physics-informed ML architectures that combine the interpretability of process-based crop models with the predictive flexibility of data-driven methods. The convergence of open data, cloud computing, and advanced ML methodologies positions agricultural science at a threshold of transformative progress in the global effort to achieve Sustainable Development Goal 2: Zero Hunger.

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